Robust Template Based Corner Detection Algorithms for Robotic Vision

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***Abstract* — Image corners encapsulate gradient changes in multiple directions. Therefore, corners are considered as efficient features for use in robotic navigation algorithms. Template based corner detection has a low computational complexity and is straightforward to implement. With the appropriate design of templates, satisfactory detection accuracy can also be achieved. In this paper, we introduce two new template based corner detection algorithms to be used to assist robot vision: the matching based corner detection, namely, MBCD; and the correlation based corner detection, namely, CBCD. These two approaches outperform existing template based approaches in the means that they reduce detection of spurious corners by considering ideal corners with at least two-pixel length on the corner arm directions. Experimental results show that the proposed algorithms detect essential corners for synthetic images and natural images satisfactorily according to human visual perception. We also examine the robustness of the two corner detection approaches in terms of the average repeatability and localization error. Since our approaches are computationally efficient, it makes these template based corner detection algorithms suitable for real time support in robotic applications. Comparisons with existing corner detection algorithms are also presented.**

Keywords – corner detection, feature tracking, robot navigation, robot vision

I. Introduction

Video cameras are the most widely used robot vision sensors. The camera captured images are analyzed by the on-board robot processors and the detected features are used to direct robot movements. Therefore, it is important to select efficient features and use fast feature detection algorithms to conserve memory resources and reduce the average response time without increasing hardware investments. Recent research on human vision shows that human eyes are sensitive to high frequency information, such as edges, and corners [1]. Accordingly, these high frequency features are selected to assist in robot vision applications. Corners are considered as more efficient features compared with edges because corners contain gradient changes in multiple directions. Furthermore, corner maps are sparser than edge maps. These characteristics make corners desirable for assisting robot vision.

Many corner detection algorithms have been presented in the past twenty years [2-6]. Generally, existing corner detection algorithms can be classified into two types: gradient based and template based methods. Gradient based methods rely on measuring the curvature of an edge that passes through a neighborhood [2, 7, 8]. They are usually formulated as functions of edge gradient strength and gradient directions. Nevertheless, the calculation of derivatives is sensitive to noise and most of the edge segments detected from the practical images are not perfectly connected to others. Therefore, these types of methods oftentimes perform unsatisfactory at localizing corners [2]. Furthermore, gradient based methods usually involve implementing a complicated gradient detection procedure, which makes it difficult for real time support in robot applications. Therefore, as a simple but effective corner detection method, template based methods are promising for improving robot vision.

Template based corner detection algorithms compare similarities between templates and image local regions. If the generated similarity measure, or so called cornerness measure, is above certain threshold, the center pixel is determined as a corner [4, 9]. Commonly used cornerness measures include the normalized correlation measure, cosine measure, and projection measure [2]. Traditionally, template based corner detection is not widely used in computer vision systems due to the fact that limited patterns of templates cannot cover all corner orientations and angles [4]. However, the template based methods respond well when the templates show similarities with the testing image patterns, or when the testing images show strong patterns such as numbers, letters or flags. Considering many robots are designed for specific tasks, such as fruit picking, room cleaning, and warehouse sorting, the similarities exist in these applications. Moreover, the intrinsic simplicity of template based methods makes it operates fast.

The goal of this work is to utilize a new set of template based corner detection algorithms to detect corners efficiently and effectively for assisting robot vision. The rest of this paper is organized as follows: Section II reviews some templates and correlation measures used in existing template based corner detection algorithms. Section III provide details of the new matching based corner detection (MBCD) and the correlation based corner detection (CBCD) algorithm. Section IV shows the experimental results on synthetic images and natural images, as well as comparisons with existing corner detection methods.

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The robustness of these two approaches is also studied in this section. The conclusions are discussed in Section V.

II. Review of Related Template Based Corner Detection Algorithms

There are two important issues of template based corner detection algorithms design: what templates to use, and how to compare the similarity between the used templates and the image's local regions. In this section, some templates and cornerness measures used in existing methods are reviewed.

The adopted types of templates are related with definitions of ideal corners. Usually template based corner detection algorithms assume right-angled corners are ideal. Therefore, rectangular templates with a sharp intensity change at the bottom right are commonly used. Some typical templates are shown in Fig. 1. Fig.1 (a) and (b) [2] are used for grayscale template corner detection. The summation of all pixel intensities in the template is zero. Fig.1 (c) [3] is used for binary template corner detection where an edge detection is applied to the grayscale image first, and the corner detection is applied on the resultant edge map. It is worth noting that the size of template is related with detection performance. Increasing the template size will decrease noise sensitivity, but also decrease localization [2]. Similarly, users have the flexibility to design other types of corner templates according to given tasks for other definitions of ideal corners.

-9	-9	-9	-9	-9
-9	-9	-9	-9	-9
-9	-9	16	16	16
-9	-9	16	16	16
-9	-9	16	16	16

(a)

-4	-4	-4
-4	5	5
-4	5	5

(b)

1	1
1	0

(c)

Figure.1 Illustrative examples of some templates used for detecting corners

Once the types of templates are determined, the next step is to compare the similarity between each template and overlapped image local regions. Some methods use direct matching to reduce the ambiguity of corner locations [3]. Some use cornerness measures and then apply appropriate threshold to abstract desired number of corners. Three cornerness measures are defined in [2]: the normalized correlation measure, the cosine measure, and the projection measure. The normalized correlation measured is defined in Eq. 1 where p and q represent the elements, α and β are the mean of the template and the image local region respectively, n is the dimension of the used template. The normalized correlation measure detects conspicuous corners. It has good localization performance, but is sensitive to noise.

$$\delta_{i,j} = \frac{\sum_{l=-k}^{k}\sum_{m=-k}^{k} p_{l,m} q_{i+l,j+m} - n^2 \alpha \beta_{i,j}}{\left(\left(\sum_{l=-k}^{k}\sum_{m=-k}^{k} p_{l,m}^2\right)\left(\sum_{l=-k}^{k}\sum_{m=-k}^{k} q_{i+l,j+m}^2 - n^2 {\beta_{i,j}}^2\right)\right)^{0.5}} \quad (1)$$

If the mean of the image sub-window β in Eq. 1 is set to zero, the cosine measure is obtained as shown in Eq. 2. This formulation represents the cosine of the angle between the two vectors P and Q, where P and Q represent the element vector of the template and the image region respectively. Compared with the correlation measure, the cosine measure is less sensitive to noise with better detection performance.

$$\delta_{i,j} = \frac{\sum_{l=-k}^{k}\sum_{m=-k}^{k} p_{l,m} q_{i+l,j+m}}{\left(\left(\sum_{l=-k}^{k}\sum_{m=-k}^{k} p_{l,m}^2\right)\left(\sum_{l=-k}^{k}\sum_{m=-k}^{k} q_{i+l,j+m}^2\right)\right)^{0.5}} \quad (2)$$

If the length of the Q vector is set to unity, the projection measure can be expressed as Eq. 3. This definition denotes the length of the projection of vector Q on vector P. The projection measure has the worst localization characteristics compared with other two measures, but it performs well on detection, even on faint corners.

$$\delta_{i,j} = \frac{\sum_{l=-k}^{k}\sum_{m=-k}^{k} p_{l,m} q_{i+l,j+m}}{\left(\sum_{l=-k}^{k}\sum_{m=-k}^{k} p_{l,m}^2\right)^{0.5}} \quad (3)$$

After the cornerness measure for each template is obtained, there are multiple ways to fuse these cornerness measures to yield one measure, such as selecting the maximum or mean of the cornerness measures obtained using each template. Oftentimes nonmaximum suppression and thresholding are then used to select the proper number of corners for given tasks.

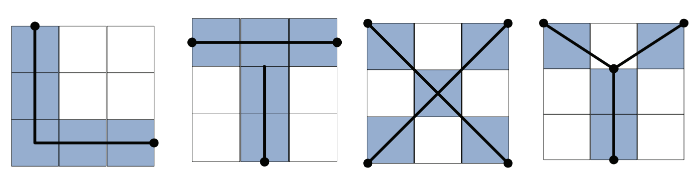
III. New Templated Based Corner Detection Algorithms

In this section, two new template corner detection algorithms, Matching Based Corner Detection (MBCD), and Correlation Based Corner Detection (CBCD) are proposed. The definition of ideal corners adopted in these template based methods is first presented. Then the basic templates used in each method are demonstrated. The method of matching corners, and the method of calculating the correlation with these templates are addressed respectively.

A. Definition of Ideal Corners

For image analysis processes that use image information, it is required that the determined corner pixels represent actual corners. Practically, actual corners are difficult to define because a corner may be varying in angles or shapes. Traditional definitions of corners are based on gradients in horizontal and vertical directions or the relative area with respect to a local region. But these definitions are ambiguous on corner locations. Also, using the traditional gradient based definitions of corners, many false positive corners can be misclassified as true corners.

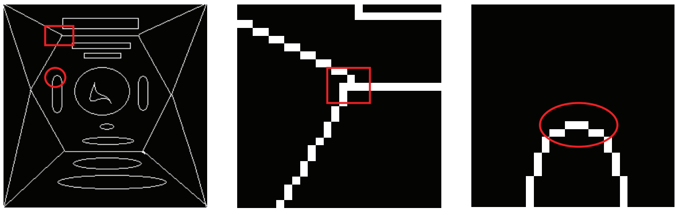
Template based methods assume ideal corners exist in the image and use correlations between templates and local regions to locate them. In the context of our template based algorithms, ideal corners are defined as the sharp corners with at least two-pixel length at corner arm directions. Some ideal corner patterns include the 'L-shape', 'T-shape', 'X-shape', and 'Y-shape' as demonstrated in Fig.2.



(a) (b) (c) (d)

Figure. 2. Basic ideal corner patterns. (a) 'L' shape; (b) 'T' shape; (c) 'X' shape; (d) 'Y' shape;

This definition emphasizes that along any direction, there should be corner edges with at least a length of two-pixels. This reduces the false detections of spurious edges. Note, that round corners are not considered as ideal corners. Illustrative examples are shown in Fig. 3 where a 'Y-shape' pattern (Fig. 3b) should be recognized as a corner while the round curve (Fig. 3c) should not.



(a) (b) (c)

Figure. 3. Examples of corner patterns. (a) Image edge map; (b) Zoom of the rectangle region: an illustrative corner patch; (c) Zoom of the circle region: an illustrative non-corner patch

B. *Corner Detection Algorithm MBCD*

In this section, we invest in designing the template matching method. As analyzed before, the more templates used, the better the detection results become. However, increasing the number of templates used will also inevitably increase operation time. A good design should create a balance between the detection performance and the operating time.

Three templates as shown in Fig. 4 are used as the basic template in the Matching Based Corner Detection (MBCD). Then, we rotate each of these templates in steps of 90 degrees to obtain 12 templates. These 12 templates cover left-handed, right-handed, and crossed 90 degree corner patterns, as well as 45 degree corners.

1	0
0	1
1	0

(a)

1	0
1	0
1	1

(b)

0	1
0	1
1	1

(c)

Figure. 4. Basic templates used in MBCD corner detection algorithm.

Instead of direct matching, the MBCD method recognizes a pixel as a corner only if at least two basic corner patterns present at that pixel location. Two examples of using the combinations of basic templates to represent ideal corner patterns are shown in Fig. 5. This tight matching reduces false positives, such as wiggly edges usually appeare in noisy or quantized images, because stronger conditions need to be met to claim a pixel as a corner.

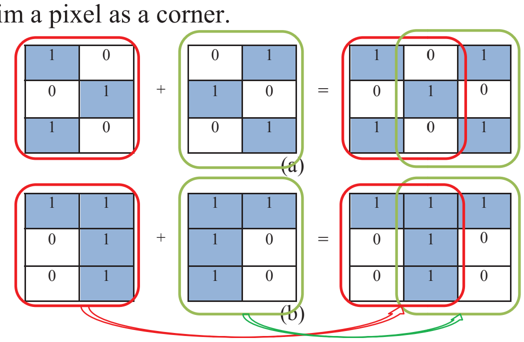


Figure. 5. Examples of using two basic corner templates to formulate ideal corners. (a) 'X' shape corner pattern; (b) 'T' shape corner pattern

Unlike other template based corner detection methods, the MBCD only compares the matching between image local regions and each template, without calculations of the correlations. Furthermore, the post-processing, such as thresholding, and non-maximum suppression steps are not required. These modifications reduce the number of parameters and also accelerate the detection speed.

C. *Corner Detection Algorithm CBCD*

The MBCD detect corners by strict matching. This approach avoids the ambiguity of corner location. However, it lacks the flexibility of determining detected number of corners. To overcome this problem, a Correlation Based Corner Detection (CBCD) detection method is presented.

In the CBCD detection method, three basic templates are used. Similarly to the templates used in the MBCD, the templates are extended to the size of 3x3 to guarantee the length of corners is at least two pixels. Nine templates are then generated by rotating Fig. 6 (b) and (c) in steps of 90 degree. We then calculate the cornerness measure using the 2D correlation between overlapping 3x3 image windows and each of the templates as shown in Eq. 1. To obtain the cornerness map, the maximum of the nine cornerness measures is used to indicate the overall cornerness for each pixel. Finally, a threshold is applied to select the final corner map. Depending on tasks, the CBCD is flexible to detect very distinctive corners, or can be used for a loose detection with variant thresholds.

1	0	1
0	1	0
1	0	1

(a)

1	0	0
1	0	0
1	1	1

(b)

0	0	1
0	0	1
1	1	1

(c)

Figure. 6. Basic templates used in CBCD corner detection algorithm.

IV. EXPERIMENTAL RESULTS

To assist feature detection in robot vision, the captured color image from a camera is first converted to grayscale, then edge detection is applied on the grayscale image and the proposed template based corner detection algorithms are applied on the resultant edge map. In this section, experiments are conducted on synthetic and natural images. The performance of MBCD and CBCD are compared with some existing algorithms including the 2x2 template corner response method [3], Harris's combined corner and edge detector [10], and Minimum Eigenvalue corner detector [11].

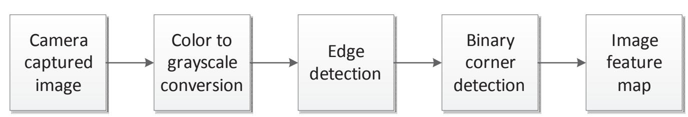


Figure. 7 Flow of the feature detection used in robot vision

Fig. 8 and Fig. 9 show the detected corners on a synthetic image and a natural image. Fig. 8 is a computer generated image with a known ground truth edge map. Fig. 9 is an image obtained from Berkeley segmentation database [12] where the ground truth edge map is evaluated by 30 human observers and averaged. From the results, it is seen that the both MBCD and CBCD achieve satisfactory corner detection and localization performance. Notice that both obtained corner maps are sparse.

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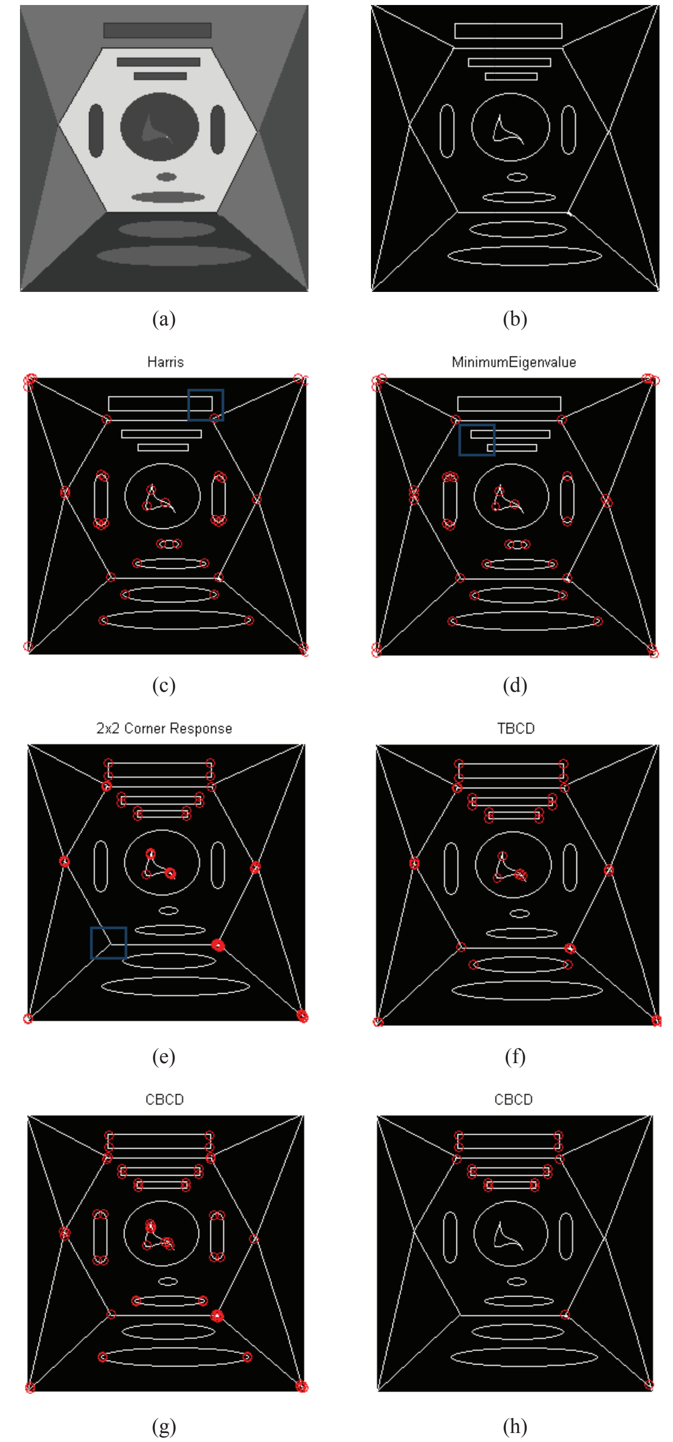

Figure. 8. Comparisons of different corner detection results on synthetic and natural images. (a) Original image; (b) Edge map used for corner detection; (c) Harris corner detection result [10]; (d) Minimum Eigenvalue corner detection result [11]; (e) 2x2 template corner response result [3]; (f) MBCD corner detection result; (g) CBCD corner detection result with threshold = 0.75; (h) CBCD corner detection result with threshold = 0.85. The detected corners are shown in the red circles.

For example, in Fig. 8, the Harris, Minimum Eigenvalue and 2x2 template corner response method miss the sharp corners shown in the blue rectangle. As a comparison, the MBCD and the CBCD detect the defined ideal corners. Note that in the

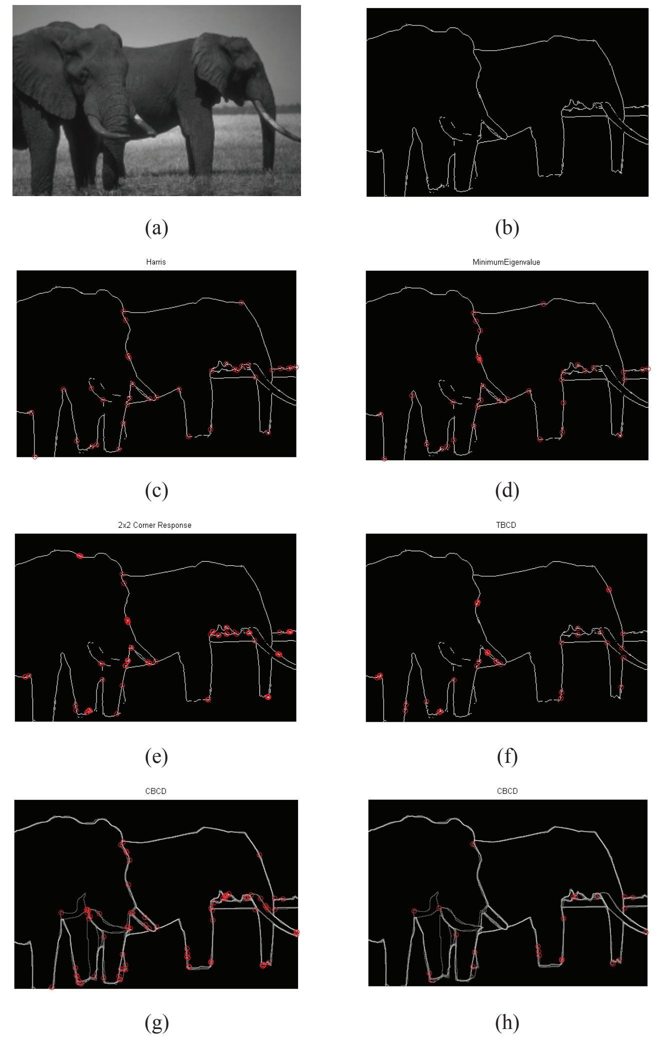

Figure. 9. Comparisons of different corner detection results on synthetic and natural images. (a) Original image; (b) Edge map used for corner detection; (c) Harris corner detection result [10]; (d) Minimum Eigenvalue corner detection result [11]; (e) 2x2 template corner response result [3]; (f) MBCD corner detection result. (g) CBCD corner detection result with threshold = 0.95; (h) CBCD corner detection result with the threshold = 0.99. The detected corners are shown in the red circles.

2x2 template corner response method, the MBCD's and the CBCD's definition of ideal corners, the round corners should not be recognized as ideal corners. It is also seen that with different level of threshold, the CBCD detects different number of corners. Similarly, in Fig. 9, the MBCD and CBCD capture essential features such as corners at the elephants' foot, nose, and tusk.

Corner detection robustness is an essential property in robot vision. The detected features from the first frame should be detectable as the same features in the next frame at the closest location. The robustness of the MBCD the CBCD is studied using the method presented in [13]. In the robustness test, 23 original images obtained from [14] are transformed using rotation (R), uniform scale (US), non-uniform scale (NUS), Combined transformations rotation and scale (RS), JPEG compression (JPEG), zero mean Gaussian noise contamination (WGN), and shearing transform (S). These image processing and geometric transformation processes

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generate 8096 testing images. The ground truth corner map is assumed to be the corner map in the original image and the corners detected from these resultant images are compared. For all these images, the average repeatability and localization error are used to denote the robustness. In Eq. 4 and Eq. 5, N_o, N_t and N_r represent the number of pixels in the original image, transformed image, and repeated in both images respectively.

$$R_{avg} = \frac{R_o + R_t}{2} = \frac{N_r}{2}\left(\frac{1}{N_o} + \frac{1}{N_t}\right) \tag{4}$$

$$Le = \sqrt{\frac{1}{N_r}\sum_{i=1}^{Nr}[(x_{ti} - x_{oi})^2 + (y_{ti} - y_{oi})^2]} \tag{5}$$

In the robustness test, the Roberts edge detection is used for both MBCD and CBCD, and the threshold for the CBCD is set to constant 0.9. The average repeatability and localization error for each type of transformation are shown in Table I and Table II. From these results, it is seen that both the MBCD and the CBCD achieve satisfactory performance of high repeatability rate (average 54.22% for MBCD, 54.80% for CBCD) and low localization error (average 1.3381 pixels for MBCD, 1.2891 pixels for CBCD).

TABLE I
ROBUSTNESS TEST RESULTS FOR MBCD ALGORITHM

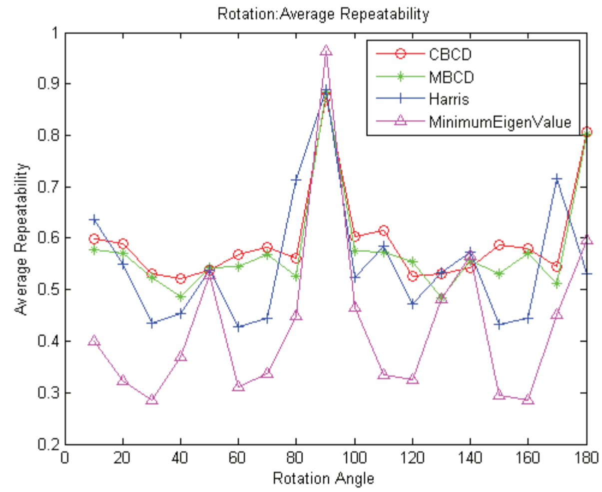
	Number of images	Average Repeatability	Average Localization Error	Average Running Time (second)
R	414	0.5771	1.5205	0.5602
US	345	0.6905	1.0497	0.3379
NUS	2093	0.6221	1.2785	0.1396
RS	3450	0.5849	1.4421	0.1764
JPEG	460	0.3986	0.9322	0.0584
WGN	230	0.3221	2.1283	0.0635
S	1104	0.5999	1.0154	0.1174
Average		0.5422	1.3381	0.1754

TABLE II
ROBUSTNESS TEST RESULTS FOR CBCD ALGORITHM

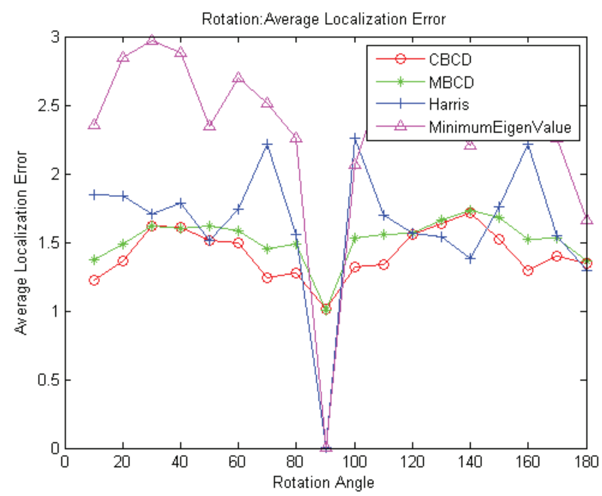
	Number of images	Average Repeatability	Average Localization Error	Average Running Time (second)
R	414	0.5950	1.4140	0.1576
US	345	0.6889	1.0492	0.1572
NUS	2093	0.6410	1.2282	0.0773
RS	3450	0.5916	1.3601	0.1568
JPEG	460	0.3919	0.9001	0.1003
WGN	230	0.3098	2.1191	0.0510
S	1104	0.6179	0.9527	0.2783
Average		0.5480	1.2891	0.1398

Two illustrative examples of the robustness performances of the MBCD, CBCD, Harris, and Minimum Eigenvalue corner detectors are shown in Fig. 10 and Fig. 11. Fig. 10 shows the average repeatability and localization error with rotation angles range from 0 to 180 degree, and Fig. 11 shows the performances with uniform scales from 0.5 to 2. Notice that almost at each degree of the transformations, the MBCD and CBCD have a greater average repeatability value and smaller localization error.

The robustness test demonstrates that the MBCD and CBCD are applicable to be used in assisting robot vision. The rotation and scaling transform simulate the camera movement and zoom. The JPEG transform and Gaussian noise contamination simulate the real world distortions during image capturing procedure. The experimental results show that the MBCD and CBCD achieve high average repeatability and low localization error under these simulated conditions.



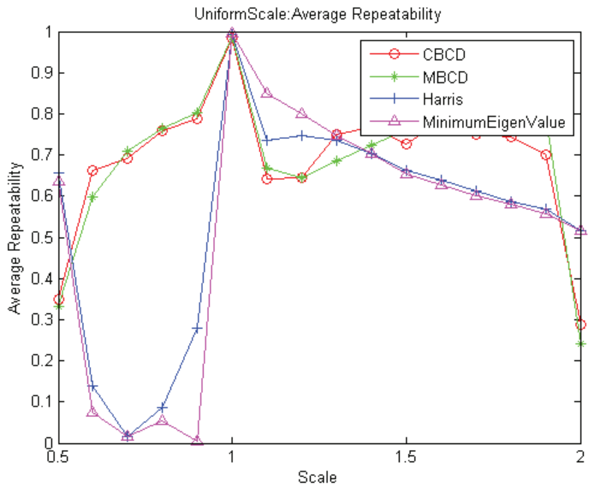
(a)



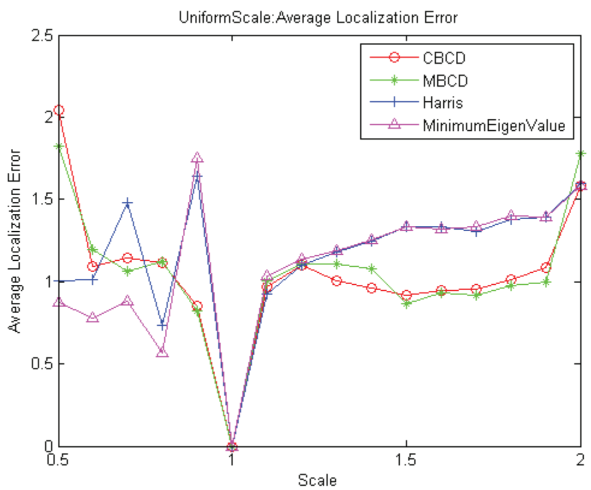
(b)

Figure. 10. (a) Average repeatability for rotation angle from 10° to 180°; (b) Average localization error for rotation angle from 10° to 180°; The red, green blue, and cyan curves correspond to the CBCD, MBCD, the Harris, and the Minimum Eigenvalue results respectively. It is seen that the CBCD and MBCD achieve greater average repeatability and lower localization error than the Harris and Minimum Eigenvalue. The performances of these four methods differ at variant rotation angles and they all achieve the best performance at the 90 degree rotation.

Table I and II also show the average image transformation and detection time for 8096 512x512 images. The testing computer features a Windows 7 system with 3.3GHz Intel Xeon CPU and 4G RAM. The experimental results show that the both methods can run in real time. This is reasonable because the MBCD detects corners by direct matching, and it does not require extra post-processing steps, while the CBCD uses three less templates than the MBCD. The characteristic of low computational cost makes these corner detection algorithms applicable for real time support in robotic applications.



(a)



(b)

Figure. 11. (a) Average repeatability for uniform scale from 0.5 to 2; (b) Average localization error for uniform scale from 0.5 to 2. The red, green blue, and cyan curves correspond to the CBCD, MBCD, the Harris, and the Minimum Eigenvalue results respectively. It is seen that the CBCD and MBCD achieve greater repeatability and lower localization error on average than the Harris and Minimum Eigenvalue. The performances of these four methods differ with variant scaling factors and they all achieve the best performance when no scaling applied.

V. CONCLUSIONS

Template based corner detection is useful for robot vision applications for its simplicity and effectiveness. In this article, we have introduced two new template based corner detection algorithms, matching based corner detection (MBCD) and correlation based corner detection (CBCD). The MBCD method utilizes 12 templates which cover 45 degree and 90 degree corners. The direct matching reduces ambiguity of the localization. Without post-processing procedures, the operation time of the MBCD method is low. The CBCD uses nine templates and compares the correlation between the templates and image local regions. With variant levels of threshold, the CBCD is able to detect corners rigorously or loosely. The templates used in both approaches guarantee that the detected corners are distinctive with at least two-pixel length in the corner arm directions. Therefore, many spurious edges are not recognized as corners and the false positives are reduced compared with other template based corner detection methods. The experimental results on synthetic images and natural images show both approaches detect corners effectively. Statistically, the robustness test also shows these two methods achieve high average repeatability and low localization error under variant image processing tasks and geometric transformations. Due to the simplicity and efficiency, this algorithm is suitable for robotic applications.

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